Optimizing Microcell Base Station Locations Using Simulated Annealing Techniques

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Abstract- **The problem of choosing the optimum locations for base stations in a microcell communications system is considered. The factors affecting optimum selection are the non-uniform service areas in complex propagation environments, the mutual coverage and interference of multiple base stations, and the service objective which is usually defined by signal level but may also be defined by delay spread for certain digital systems. This optimization problem is addressed here using simulated annealing (SA) techniques which offer a method to achieve near optimum solutions to complex combinatorial optimization problems. This research shows that SA is a viable approach for handling practical base station siting problems in an urban microcell environment.**

1. Introduction

The cost and network complexity of a microcellular communication system is strongly dependent on the number of base stations (BS) required to achieve the system operator's service objectives. There is consequently a strong incentive to develop system planning tools which can be used to minimize the number and optimize the location of the system base stations. For a typical city, the service objective function may be quite complex and detailed, and the possible combinations of base stations too numerous to examine exhaustively. An automated technique for minimizing the number of required base stations, and choosing the optimum location for those base stations, would be a worthwhile tool.

A useful optimization tool for BS siting problems must therefore address several special factors:

- The propagation environment which determines the service area will be quite complicated. In urban areas the service area will be controlled by the locations of the buildings and streets. In suburban areas, foliage and terrain, as well as buildings, will also affect the service area.
- The objective function may not be uniform. The system operator may require higher quality, more reliability, or multiple servers for certain parts of the service area and not others. The optimization tool must therefore be able to handle uniquely-weighted, non-homogenous objective functions.
- The possible system configuration set is quite large and also may not be uniform. Possible BS locations may be restricted to certain locations (i.e. only on lampposts), or excluded from other locations for engineering, administrative, or social reasons (i.e., no BS's in the lake or park. etc.)

These requirements indicate a tool which can handle detailed combinatorial optimization problems. For BS siting, the current ad-hoc approach is to more or less make "educated guesses" by inspecting maps of the intended service area. In macrocell systems, most often the BS's are located at the tops of mountains or buildings. The potential coverage from such candidate sites is predicted and plotted using commonly available software propagation tools. The results are then analyzed and changes in BS configurations manually made to get the required service with the minimum number of transmitters and associated construction and site costs. Directional and sectorized antennas may also be used to focus service or enhance frequency re-use.

For microcell systems, the approach is largely the same, although the "educated guess" can be automated to some extent by using a software algorithm to start at a given transmitter location and "explore" along streets away from the transmitter until the predicted signal is sufficiently weak that another BS is needed. For very limited systems, especially those in cities with regular street grids, this approach has some value. For larger systems in cities with many irregular streets and block arrangements, such an approach rapidly becomes unwieldy, and certainly is not a systematic approach toward an optimum BS configuration.

In any optimization problem there is a desired objective function in which a variety of conditions must be si-

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multaneously satisfied. A particular system configuration is then selected as a starting point and the difference between the desired objective and the degree to which the current configuration satisfies the conditions is calculated. This difference is the error or cost function. Optimization seeks to minimize this error. For simple, discrete cases, one could simply exhaustively try every possible system configuration and chose the one with the lowest error. For more complicated problems, the computation time would be prohibitive.

Traditional "steepest descent" optimization techniques seek this solution by making small incremental changes in the system configuration to find those changes which reduce the error. Those changes which most rapidly reduce the error are made, creating a new system configuration. Using this new configuration as a starting point, incremental changes are once again tried to find a direction to move toward an even lower error. In essence, the system parameters are moving around on a multi-dimensional error surface seeking the fastest way downhill, or "steepest descent", to a minimum error. Many variations of this basics technique have been used in which the incremental parameter changes are adaptively adjusted based on certain learning done while moving around on the error surface. The classic difficulty with the steepest descent approach is getting stuck in a local minimum. From a local minimum, all directions on the error surface are "uphill" and represent higher error or cost. The steepest descent approach will terminate at this point assuming it has arrived at the optimum solution.

Another approach to optimization is simulated annealing, so-named because the process is strongly analogous to the annealing process for creating a durable metal by systematically cooling and re-heating it. SA techniques were originally employed in thermodynamics [1]. More recently they have been employed to allocate silicon real estate for circuit elements [2], and a variety of other problems in image processing, coding algorithm design, and two specific problems in mobile radio [3],[4].

The balance of this paper describes the application of SA to the base station optimization problem in a hypothetical city grid using a simplified propagation model. Selecting SA starting point temperatures and cooling schedules which are customized to this type of problem are also discussed. Practical performance examples using SA for a single and for a four transmitter system are presented.

2. Simulated Annealing

In recent years SA has received more interest as an optimization technique mainly because the nature of the problems to be addressed have become more complicated and because the necessary computer processing power is more readily available. A few references are now available which describe the techniques and mathematics of SA in detail [5],[6]. It is not the intent here to present a detailed discussion of SA, but rather to highlight those features of the method which will allow its adaptation to the base station siting problem.

Simulated annealing starts with an initial system configuration, s, from a configuration set S which may be extremely large. It can be assumed that the initial configuration is not optimum so that there is some difference between it and the optimum configuration. The associated error or cost for this difference is $C(s)$. From this starting point *random* changes are made in the system parameters to arrive at a new configuration s' and associated cost $C(s')$. The configurations which can be arrived at from the starting configuration s are known as the neighborhood structure N on S. The neighborhood $N(s)$ controls the allowed transitions from any given state s. The possible transitions are determined by how large the allowed random changes are. In SA, the allowed random changes are analogous to the temperature of an annealing process. The higher the temperature, the greater the magnitude of the allowed random changes, just as molecules in metal at high temperature have more energy available to permit greater mobility. Greater mobility for the molecules leads to a greater range of configuration transitions.

After a random change from s to s', the process evaluates the new cost function $C(s')$. If the cost is lower, (i.e. $C(s') \le C(s)$), the transition is accepted and the process is repeated. If the cost is higher, SA allows for accepting the transition with probability given by $P = \min\{1, \exp(-(C(s') - C(s)) / T)\}$, where T is the "temperature". This is known as the Metropolis criteria [1]. The probability of accepting an uphill or higher cost transition decreases with decreasing temperature and increasing transition cost difference. SA avoids getting stuck in local minima both because uphill moves are occasionally permitted and because the random changes in configurations, especially at higher temperatures, allow the process to jump out of local minima.

At any given temperature level, an equilibrium state can be achieved if an infinite number of transitions are permitted. Since allowing an infinite number of transitions at each temperature is not possible from a practical point of view, a convergence on equilibrium is usually sought. When the process is sufficiently close to equilibrium, the temperature is lowered to the next level and the process is repeated to approach equilibrium at this new temperature. As the temperature is decreased, the magnitude of the random configuration changes is also decreased along with the range of possible transitions (N). The relevant features of the SA process which must therefore be selected are 1) the initial temperature, 2) the cooling schedule for lowering the temperature, 3) the definition for equilibrium, and 4) the point at which the SA process stops.

The literature [5],[7], contains some methods for choosing these factors in a systematic way. However, for any particular problem a certain amount of experience and intuition can be applied which may work better than a formal approach. For example, with the microcell base station siting problem in an urban environment, it is desirable to chose an initial temperature which permits with reasonably high probability a base station to move from one street over to the next street. The typical city block size would then be incorporated in setting the initial temperature. As the temperature is lowered, high probability transitions would be confined to moves along a given street on the same block. The success of using the SA process is largely determined by how skillfully the four parameters listed above are chosen for any particular optimization problem.

3. Propagation Model

Simulating annealing is a computationally intensive process in which a very large number of possible system configurations must be evaluated. When seeking optimum coverage for a microcell system with the minimum number of transmitters, the propagation model which is used to determine coverage for a base station will be extensively exercised and must be efficient.

Current propagation models for microcell systems fall into two categories - empirical and deterministic. Empirical models are based on measurements and usually involve some kind of inverse function of distance, d, where the exponent of d (or log multiplier) is adjusted for the propagation conditions and whether the transmitter and receiver are in line-of-sight (LOS) or non-LOS conditions. A typical model for path loss, P_L, with LOS conditions constructed as intermediate between the upper and lower bounds (eqns. (1) and (2)) in [8] is:

$$P_L = L_b + 10 + 20\log(d / R_b) \quad d \le R_b \qquad (1a)$$

$$P_L = L_b + 10 + 40\log(d / R_b) \quad d > R_b \qquad (1b)$$

where: $R_b = \dfrac{4h_b h_m}{\lambda}$ and

$$L_b = \left| 20\log\left(\frac{\lambda^2}{8\pi h_m h_b}\right) \right|$$

The parameters h_m and h_b are the heights above ground for the mobile and base station antennas, respectively, and R_b is the so-called "breakpoint distance" where the slope of the path loss versus distance line changes. These equations are valid for vertical polarization.

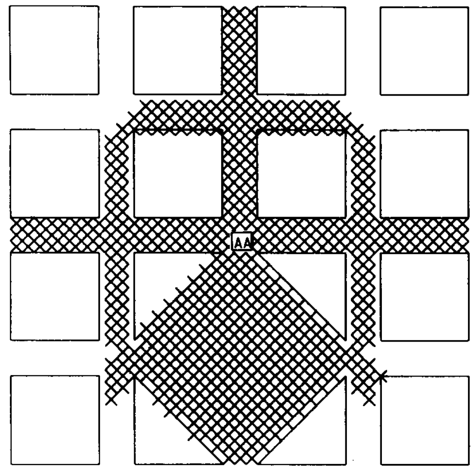

Figure 1 - Single transmitter optimization result

A second approach to propagation modeling in microcells which has recently received considerable attention is deterministic ray-tracing. Such models are described in [9],[10], [11], [12] and a number of other places. Deterministic ray-tracing models have the advantage of being site-specific in that particular characteristics of the propagation environment can be taken into account. They also inherently provide digital pulse delay spread information which could be used as a system optimization objective instead of (or in addition to) signal strength. The serious drawback to ray-tracing is that of itself it is computationally intensive. Performing an SA optimization for a practical multi-station system using full ray-tracing would be a daunting computational task.

For the investigations conducted here, the simplified empirical LOS model in (1) was used for LOS conditions. For non-LOS conditions, 25 dB was added to the path loss computed in (1). It is recognized that these are simplifying assumptions about path loss which may not be valid in many actual cases. However, our primary objective here is to explore the application of the SA technique to the BS siting problem. To that end, the simple propagation model outlined above is sufficiently realistic.

4. BS Coverage Optimization

Figure 1 shows the hypothetical urban city environment which was used to experiment with the SA optimization technique. The transitions from one state to the next are accomplished by allowing each BS to make a random moves in the x and y direction. The magnitude of the random x,y moves is set by the current "temperature", or variance of the Gaussian distribution from which the random move values are taken. If the new x,y location is a permitted BS site given whatever constraints exist, then it is accepted as a valid proposal. This process is repeated for each BS. Once all BS's have new, permitted locations, this then constitutes a new system "state" and the SA process proceeds to evaluate the cost associated with this state. The new system state will always be accepted if the cost is lower; it will sometimes be accepted if the cost is higher as described in Section 2. The parameters which control the SA process in this research are as follows:

Starting Temperature: - The starting temperature T_0 (the variance of the x,y transmitter moves) was set to 80 meters for the street grid shown in Figure 1. Given the block size, this results in a high probability of a transmitter being able to jump from one street to the next at the starting temperature.

Cooling Schedule: The cooling schedule was set such that $T_k = 0.8\ T_{k-1}$, $k > 0$.

Equilibrium: For this research, a formal convergence on an equilibrium distribution was not attempted. Instead, the simple approach of permitting 100 state transitions at each temperature level was used.

Stopping Point or Final Temperature: The stopping point for the optimization is defined by either 1) the point when the error or cost function is reduced to zero, or 2) the point when the maximum and minimum costs are equal to the maximum single change in cost.

Cost Function: The cost value of a particular state was computed as the sum of the squares of the difference between the power level as each grid point and the desired (objective) power level for those points below the desired power level. If the power level at a point was above the objective, the error or cost was considered to be zero.

Uphill Move Acceptance Probability: Since the units of cost and "temperature" in this case are very different, a normalized "uphill" movement acceptance probability was defined as follows:

$$P = \min\{1, \exp(-A / B)\} \qquad (2)$$

where $$A = (C(s') - C(s)) / C(s) \qquad (3)$$

and $$B = (T_k / T_0)^2 \qquad (4)$$

As a first test of the SA technique, a single transmitter was placed on the outside edge of the street grid shown in Figure 1. The transmitter ERP was set to -20 dBW. The objective function was defined as achieving at least -100 dBmW power level at the points in a 10 meter grid covering all the streets in Figure 1. The possible transmitter moves were also confined to street locations.

The optimization was started and the transitions (transmitter moves) graphically observed on the computer screen as the optimization proceeded. This simple test was used because the optimum BS location could be readily found by an exhaustive analysis of all the possible grid locations. Several different starting locations were tried for the single transmitter. In each case the optimization arrived at a final position that was within a few meters of the optimum location.

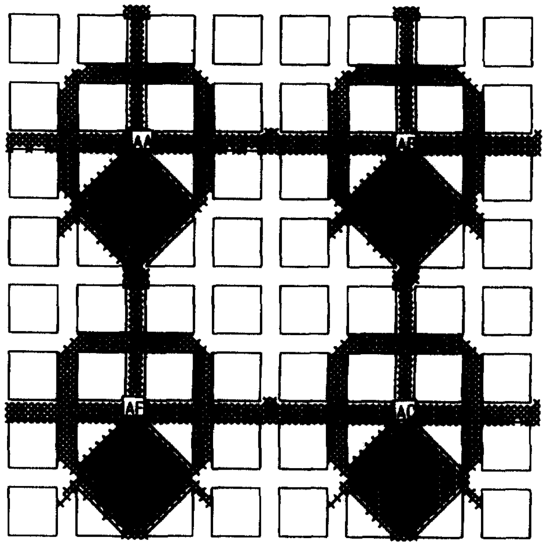

Figure 2 - Four BS study optimizing signal levels.

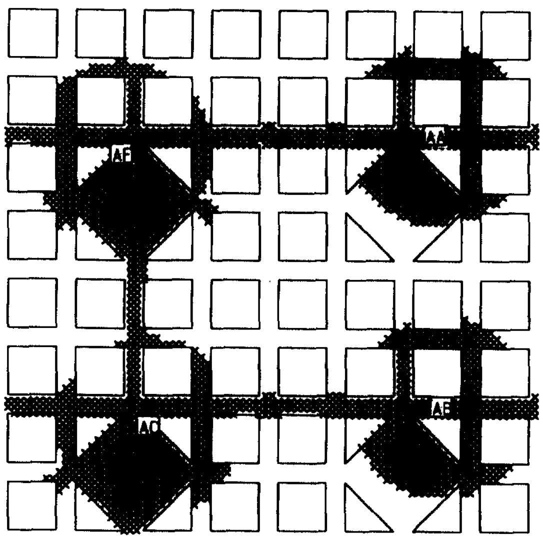

Figure 3 - Four BS study optimizing signal levels and C/I ratios.

It should be noted that unlike physical systems, a computer SA process has memory so that it can keep a record of the lowest cost state thus far achieved. If the transmitter position finally arrived at after all the transitions at the lowest temperature was not the lowest cost among all the states tried, the final step in the SA process would be a simple step to the lowest cost state encountered in its various attempts. This occurred in about 15 percent of the single transmitter attempts.

A more realistic and valid test is a multi-transmitter case in which the optimum positions are not known. For this purpose, the grid in Figure 2 was used with four BS transmitters. At the start of the optimization, all four transmitters where positioned together at the center of the street grid. The optimization was then run on a 60 MHz Pentium™ class PC and took approximately 25 hours to reach the final temperature. The final positions of the transmitters are shown in Figure 2 with the resulting coverage prediction using the model described in Section 3. Different starting states will yield different final BS configurations with overall costs approximately the same, indicating that near-optimum solutions are not unique.

5. Other Objective Functions

The SA example presented here optimized coverage for a set of BS transmitters. However, there may circumstances where mean signal level is not the most important factor in determining overall performance.

Depending on the system type, minimizing interference may be the most stringent requirement on system performance. In this case, signal levels are still computed as in the example cited above, but instead the ratio of levels at each point in the objective grid is assessed with a view toward achieving at least 10 dB carrier to interference ratio (CIR) at each point. The four transmitter SA study given above was re-run with the objective of achieving 10 dB CIR *and* -100 dBmW signal level at every point in the grid. The final locations of the four transmitters are shown in Figure 3. The SA process could also be applied in which a weighting function was applied to either the CIR or signal level objective. Directional, or adaptive, antennas [13] could also be added to the optimization mix, with an attendant increase in complexity and execution time.

For wideband digital systems, choosing a transmitter configuration which minimizes RMS delay spread might be a more important objective in achieving reliable system performance. To calculate delay spread, however, some notion of the relative time delay of the arriving signal reflections is necessary so that ray-tracing methods like those discussed in [9], [10], and [11] must be employed. Given the computation burden of such methods, it would be a challenge to use SA to arrive at a system design with any practical computer resources. Current research is underway to find more streamlined methods to estimate RMS delay spread than full ray-tracing. Such methods may be the key which allow SA to be feasible for optimizing overall RMS delay spread throughout a system.

6. Conclusions

The problem of optimum siting of base station transmitters in a microcell or PCS system has been addressed using the simulated annealing optimization technique. This approach is well-suited to complex combinatorial optimization problems where the objective function and possible system states can be discretely defined.

Using a simple propagation model, it was shown that plausibly optimum transmitter sites can be successfully selected automatically regardless of how inadvertent the starting positions of the transmitters are.

Although the SA process is computationally demanding, its use on fast PC's or workstations is feasible. As a result, it is potentially useful as a practical approach in real design efforts for a wide range of PCS and microcell systems.

7. References

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